MIQ
Understanding a Machine through Multiple Perspectives Analysis

I. C. Ulinwa
School of Education, Walden University
Minneapolis, Minnesota
iulinwa@waldenu.edu

ABSTRACT
Machine intelligence is a phenomenal event with distinctive aspects that can be discriminatorily measured with specialized instruments. A good measurement instrument should incorporate technical, humanity, and institutional scales to capture features in diverse but correlated domains that shape machine intelligence. This is only possible through a holistic method such as the multiple perspectives inquiring system (TOP). This paper demonstrates that such distinctive measures correlatively advance machine intelligence quotient (MIQ) by bringing to bear clear scales to measure and interpret machine intelligence.

KEYWORDS: MIQ, TOP, machine intelligence, holistic measurement

1. INTRODUCTION

Machine intelligence is a phenomenal event with distinctive aspects that can be discriminatorily measured with specialized instruments. For instance, adaptive and novelty problem-confirming instruments confirm or disconfirm a phenomenon whereas illumination instruments uncover type 1 or 2 error that could invalidate a measurement. Hypothesis instruments, on the other hand, probe solution spaces. It follows that hypothesis instruments increasingly axiomize solution spaces and more intuitive than an overly discipline interpretative analysis that attempts to extend a measurement domain.

Although [37] and [32] among other methodologists posited an exploratory, explanatory or a descriptive measurement, holistic machine intelligence measurement instruments should not be grounded on a single type approach. Rather, the instruments must be designed to analyze the manifest of constructive and interpretive contextual anchors that reflect how experience of the world is represented. It follows that such diverse evidence sources usually converge immensely to axiomize solution spaces.

Conceivably, machine intelligence measurement school lacks certain necessary instrumentation resources. Current methods such as autonomy and performance measures are very unitary and insufficient and could be rigorous hyperbolas that exclude any of the perspectives to be introduced in this article. Such conventional instruments lead to an incomplete explanation, theory, and comprehension.

2. MULTIPLE PERSPECTIVES INQUIRING ANALYSIS

Machine intelligence measurement instruments should incorporate technical, humanity, and institutional scales to capture features in diverse but correlated domains. This is only possible through a holistic method such as the multiple perspectives inquiring system (TOP).

The multiple perspectives inquiring analysis is relative to all the aforementioned schools. It minimizes statistical biases that are common in only quantitative science and practice. Secondly, it discovers underlying perspective meanings that affect machine intelligence science. Three, it ratifies theory and data anchors that could ground on more than one perspective. Four, it insures that the bases of any solution and thesis are within the intelligence domain peer experts and consumers recognize.

The use of TOP for machine intelligence measure is grounded on the derivatives set forth by [24], [25], [31], [36], and [44] because it is imperative to lay down a comprehensive and standard method for understanding and measuring intelligence of machines. It follows that the TOP brings to bear in any given problem inquiry, Technical, Organizational, and Personal factors [24].

2. 1 Technical Filter (T)

The T perspective is a quantitative science with an objective to numerically justify every means and results. It uses measurement science to isolate, abstract, idealize, and simplify problems into solutions [24]. For a machine intelligence measurement to be an important scientific function, according to this perspective, results must be quantitatively analyzed, interpreted, and reported.

A five-theoretical approach classified with a [6] topology is crucial to this perspective [7], [11]. The topology, with a distinct name of a philosopher such as Leibniz, Locke, Kant, Hegel, and Singer is summarized as following. *Leibnizian* analysis is grounded on the principle that truth is analytical and can be mathematically reduced into a solution space. *Lockean* analysis emphasizes that truth is experimental and in any given problem peer experts' scientific opinion determines if a solution is acceptable or not.

On one hand, *Kantian* inquiring analysis rests on the assumption that truth is synthetic and only through two complementary solution models. Null and alternative hypotheses are developed for accepting or rejecting any practice that is hard to be studied with the Lockean or the Leibnzian method. On another hand, *Hegelian* analysis is grounded on the premise that truth is conflictual and only through formulation of antithetical representation. The *Singerian* inquiring analysis emphasizes on pragmatic analysis of truth that is relative to the general purpose and objective of an inquiry [10], [24].

2.2 Organizational Filter (O)

The O perspective relies on policies and ethics. For example, it insures that measurements are within acceptable scientific practices, constraints, and constitution. It determines the standard and conditions for rigorous issues.

It follows that complexity that arises from organizational decisions is because individuals support group decisions they would rather not make personally [24]. The O perspective purports that a strong culture produces results [15], [33]. Note that culture could implicate any acceptance or rejection of machine intelligence and measures.

Moreover, believable myths play an important role in every organization. Myths are narrative sources to anchor the present in the past. Myths include the ability to express, explain, maintain solidarity and stability, legitimize, and remedy contradiction [5]. Generally, the O perspective does not seek optimal solution but emphasizes on compromise and routines.

2.3 Personal Filter (P)

The personal perspective is very subtle compared to the others. It brings to bear the psychology, ethics, and sociology of those whose decisions affect a system, and these factors are inseparable from any model [10], [24]. It brings human persona or the "eye" of an individual into measurement science and practice. It is the unique insight and intuition for analysis [24].

3. THE PERSPECTIVES ON MACHINE INTELLIGENCE MEASURE

Measurement in science has a long tradition even though the degrees to which things are measured differentiate a well-developed science such as physics from some of the less-well-developed ones like psychology or sociology [1]. The measurement for length--the meter--was properly defined in 1889 whereas measuring temperature was more complicated until Fahrenheit in 1714 and Celsius in 1742 introduced the measurement intervals for temperature, which graduate from one point to another [23].

Similarly, Rene Descartes implicitly introduced the notion of measuring machine intelligence in 1637 by articulating some ideas for disproving machine intelligence before Alan Turing proposed a formal measure of machine intelligence in 1950 [40]. Among other types of measurement is fuzzy logic, which extends classical logic by permitting linguistic variables to take values on interval between zero and one [41], [42], [43]. The following are some of the current instruments these perspectives use to measure machine intelligence.

3.1 Technical Filter (T)

[27] posited a vector of intelligence from which one could derive measurable resources. [21] argued that the vector might not represent the essence of machine intelligence despite its comprehensiveness. Setting aside the list [21] proposed a three-premise, although questionable, universal problem-solving capability measure. The model sought solutions that are relative to goal, time, and resource relevance.

A universal problem-solving capability at time t or relative to learning and economic factors is the core of the model. It follows from [21] assumption that machine intelligence measure should be as following:

$$tMIQ = \max \int_{t_o}^{t} dMIQ(g,t_o)dt / t\max \qquad (1)$$

Where max is maximum time that the tMIQ is realized. A learning rate can be obtained from the following formula:

$$\max \int_{l_o}^{l} dMIQ(g,t_o)dt / t\max \qquad (2)$$

Integrating $\int_{g\in G} MIQ(g,t_0)$ and $\int_{l_o}^{l} dMIQ(g,t_o)dt$ (3)

or $\int_{g\in G} Max[MIQ(g,t_0) + \int_{l_o}^{l} dMIQ(g,t)dt]dg$ (4)

gives a universal machine intelligence quotient with respect to problem solving capability where the g is a goal in a set of goals.

Although the model is promising, unknown to [21] it only belongs to the T class of measures. On the other hand and contrary to [21] objection, a lot can be discovered if TOP is used to streamline and analyze the vector of intelligence. Intuitively, this warrants further and a careful examination of the vector with TOP model.

A branch of this perspective prefers information theoretic measure. For instance, [35] proposed a monotonic nonlinear scale. The logarithmic scale ensures human-like intelligence of which a net result is further measured with a percentage scale [35].

As a learning, and information- theoretic scale, supervised with a look-up table and unsupervised learning constitute the MIQ instrumentation. Emphasizing on Botzmann entropy, [35] noted that systems that are below 50% percentile are dumber whereas those above the divide or dyadic basis are intelligent.

Despite the variations, probabilistically or possibilitically, the methods are derivatives of Shannon communication postulation applied to machine intelligence. Other schools endorsed performance and autonomy as measures of a system's intelligence.

3.2 Organizational Filter (O)

The O perspective grounds measures of machine intelligence on private economics and public sector legislation. Foremost, all machines like other goods are subject to public sector scrutiny. The scrutiny involves complying with a set of legislative guidelines in or related market. Legislation scale, therefore, is a measure of compliance of goods to public legislation.

Legislation could constrain the capability or nature of intelligence of machines. It follows that the nature of legislation affects the validity and reliability of legislation measure, because of the likelihood of compromising scientific standards with special interest groups' desire. For instance, an unmanned defense craft may be designed to shoot at enemies on sight, however legislation may be enacted not to allow autonomous action unless human-live operators approve the action to avoid civilian casualties.

Private economic condition and factors that affect it have been the concern of the economics school. This school recognizes the consequences of machine intelligence to human capital. [30] noted the similar but to the effects of unintelligent machines on labor wages. Although [34] implied that machine intelligence would continue to raise the demand for skilled labor, [14] and [22] insisted that machines, perhaps the intelligent ones, could substitute skilled labor. That machine intelligence will continue to complement human capital until it substitutes it like modern transportation substituted horses [28]. It seems then that a measure of intelligent machines should reflect the rate human, perhaps economic, skills are replaced or complemented by machines.

Imagine for instance a person who makes a pair of shoes in a day. If there is an intelligent machine that efficiently makes thirty in a day than the owner, he or she is better off to employ the machine, instead of toiling in protest against the machine. This is the essence of Adam Smith's concept of division of labor [13].

Using a modified neo-classic growth model with diminishing returns such as the Cobb-Douglas production, [12] posited Y = Y(A,L,K,,M) = $AL^{\alpha}K^{\beta}M^{\Upsilon}$, where Y is rate of product, A is level of technology, L is labor, M is computer capital, and K is education or training. The marginal products, partial derivatives of Y with respect to all inputs, satisfy $Y_L = a\frac{Y}{L}, Y_k = b\frac{Y}{K}$, and $Y_M = a\frac{Y}{M}$ (5)

The marginal products are Y_L, Y_k, and Y_M. In competitive market, asserted [12] each will receive its marginal product of which the total marginal product is equal to the total average product. Thus, $\alpha + \beta + \Upsilon = 1$. The implication is that each of α, β, and Υ describes its fraction of the production revenue.

To allow for machine intelligence, [12] assumed instead that $L = H + U$ and $\alpha + \beta + \Upsilon < 1$ where H is human labor and U is machine intelligence labor, enough to replace human capital. [12] model implicated machine intelligence for it speculated that few computers would be bought if price were high. If price falls or because $Y_L < Y_M$, contribution of intelligent machines to production will be unattractive.

On the other hand, if $U > 0$, that is, $Y_L = Y_M$ then wages will fall as price of computer falls, unless interest rate rises quickly. [12] hinted that the proportionality between wages and per intelligent production is due to intelligent population growing faster than total production.

It follows that the model has Mathusian's implications for population and wages. That wages will continue to rise but will drastically decline. The model showed that "wholesale" use of intelligent machines can increase economic growth rate greater than order of magnitude. The main assumption is that total population of intelligent machines can grow at a desired rate that matches demand of human labor.

[21] recognized this class of measure when they pondered on microeconomics aspects of intelligent systems. They questioned if resources or cost for building a system should be a significant measure. [39] articulated the necessity to include the economic value of intelligence in terms of cost benefit analysis.

The drawback is the numerous ways machine could be measured economically using macroeconomic or microeconomic factors. Intuitively, macroeconomic analysis should be set aside for legislation criteria. On another hand, microeconomics is justifiable given the essence of machine intelligence measure: cost of production and productivity of the intelligent machine.

Given these concerns, measures of machine intelligence should reflect to the degree of compliance to public legislation in addition to machinery and economics efficiency. Meta-systematically, an organizational measure of machine intelligence is a function of public legislation P_L and private sector investment P_V. Or $MI_o = f\{P_L, P_V\}$. As a bi-directional scale, it should indicate the compliance to public legislation whereas the other should mark the private economic measure. This is similar to negative-positive thermometer scaling.

3.3 Personal Filter (P)

Although, some scholars like [27] dismissed Turing test on the ground of incompleteness, the test verified and compared computational with human intelligence [20]. The test is the first conceptualized P perspective view of machine intelligence and measure. It set the standard for determining if a given artificial device is intelligent from humanity point of view [2], [3], [4], [26], [29], [29].

This thought-model is similar to a human interrogator and a person and a machine. The interrogator interacts with the person and the machine through an input device such as a keyboard. The interrogator is not told which of the participant is human and which is the machine; this minimizes or eliminates interviewing bias against the machine. The machine is then considered intelligent if for any reason, after a question and answer session, the interviewer could not reliably identify it.

Another measure is the "Chinese Room". [32] described a Chinese room concept for testing machine awareness, in which a person who does not understand Chinese but speaks English is locked in a Chinese-room where a series of Chinese stories are shown from the outside. He or she is given in English, written behavioral and response instructions for responding to questions about the stories that are in Chinese symbols (each instruction is mapped to the appropriate Chinese story symbol). Moreover, the person is not allowed any other form of information from the outside but is allowed only to manipulate both the symbol and the appropriate story by referencing the instruction, that directs each answer to a corresponding question and story. He or she is also permitted to answer to those outside the room through a type of opening, and also expected to answer in the form of yes or no format making it possible to be mapped into a computer program.

[32] contended that machines lack awareness of what is going on, much like the person in the Chinese room who could not correctly answer questions about the stories without understanding the stories. The person can only act on the given answer manual in the same way machines act on algorithms. Machines, without understanding, manipulate programs by acting on algorithms.

The nature of Searle test, therefore, brings to bear ideas about factors of machine intelligence to be measured. We need not measure awareness rather factors and action we as human understand as showing intelligence should be of immense concern.

Therefore, one can not summarily dismiss the essence of Turing test, for it explains machine intelligence from the P perspective, like the T explains with optimization benchmark or the O with economic and legislation factors.

Variations of the P abound in the literature, some with new insights and others extending Turing test. For example, [16], [17], [18] and [19] were devoted on extending Turing test whereas [8] and [9] among others offered different P measurements.

.

4. SOME IMPLICATIONS

By no means are the cited cases the only measures of machine intelligence quotient. They illustrate possible classification of topical measurement instruments.

Although [24] recommended cross-cueing the perspectives for an in dept analysis, the nature of machine intelligence permits otherwise. By not cross-cueing the perspectives each measure conveys a different assumption of the phenomenon and implicitly correlating with the other interpretations and meanings.

Figure 1, an assumed intelligent thermometer is a good example. For the sake of an argument, assume that the instrument is an intelligent one, has Fahrenheit and Celsius scales plus a fuzzified scale.

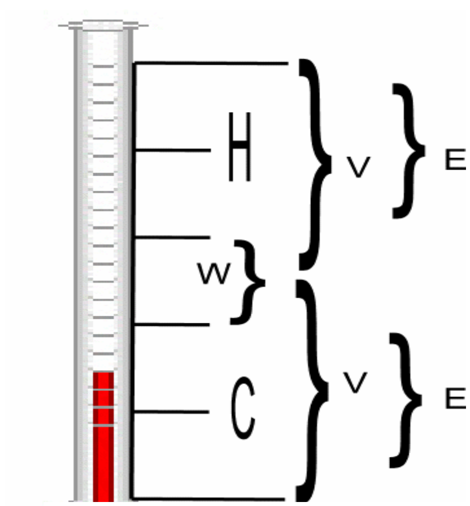

Figure 1. Intelligent Thermometer

The fuzzified scale is a linguistic one, with warm (w), cool (C), hot (H), very cold (V) or very hot (V), and extremely cold (E) or extremely hot (E) as linguistic variables. Points below the middle point in the warm region are literally considered cold and those above it are hot.

The instrument's overall performance then becomes the T measure of the intelligence. The O measure would emphasize on how accurately the marks are the true representation of weather conditions and scientific measurement guidelines. The O would determine if the instrument is within any legislative guideline and is not scientifically misleading.

One concern should be to determine if the instrument could explode if at the maximum temperature level. Is the scale conveying the information the manufacturers claim? Other similar questions could subjectively exploit other legislation compliance. A normalized legislation fine could be used to measure conformity. O also scales microeconomic cost of production. The assumptions include maximizing profit and other returns against investment and materials of production.

The P, on one hand, with an implicit linguistic scale interprets weather conditions as warm, cool, hot, very cold or hot, and extremely cold or hot. The exact point for the regions has no bearing what so ever. To be P meaningful, the indications must be relative to human interpretation of weather conditions irrespective of the scientific measurement in use.

As one could see from this elementary introduction, TOP is a measure that allows the interpretation of "Blind men and the elephant" type phenomena. Each observer clings onto the part he or she sees but contributes immensely to the interpretation and meanings of the whole system. [38] demonstrated the essence of TOP on the nature of a primeval unmanned aircraft.

A procedural suggestion is to normalize all measures using standard fuzzy methods. Normalizing the measures allows one to understand what are at stake. For example, an MIQ of {.9, .7, .6} would mean that performance is technically .9, organizationally .7 in legislation compliance, and .6 on humanistic scale. The P measure implies that the systems behavior is similar to a certain quality humans could consider as showing intelligence.

This procedural suggestion does not underscore the use of performance or productivity measures for the T perspective, nor adopting any type of legislative scaling, or using personal perspective similar to the Turing test or its extensions. It is grounded on the idea that to fully understand machine intelligence the perspectives must be correlatively measured independently. The P, for example, allows individual consumer to evaluate the system relative but in comparison to the manufacturers' claim.

5. Reference

[1] Abreu, F. B. (1993). Metrics for object-oriented environment. proceedings of the Third International Conference on Software Quality, Lake Tahoe, Nevada.

[2] Arbib, M. A. (1965). Brains, machines, and mathematics. New York, NY, McGraw-Hill Book Company.

[3] Balkenius, C. (1995). Natural intelligence in artificial creatures. Lund, Sweden, Lund University Press.

[4] Boden, M. A., Ed. (1990). The philosophy of artificial intelligence. Oxford, Oxford University Press.

[5] Bolman, L. G. and T. E. Deal (1984). Modern approaches to understanding and managing organizations. San Francisco, Jossey-Bass Publishing.

[6] Churchman, C. W. (1971). The Design of inquiring systems. New York, New York, Basic Books.

[7] Courtney, J. F., d. T. Croasdell, et al. (1998). Inquiring organization, Foundation of Information Systems. 2000.

[8] Falqueto, J., W. Lima, et al. (2001). The Measurement of artificial intelligence-An IQ for machines? IASTED International Conference on Modelling, Simulation and Control, Innsbruck, Austria, Minutes Press, Calgary, Zurich.

[9] Finkelstein, R. (2000). A method of evaluating the IQ of intelligent systems. PerMIS: Workshop on Performance Metrics for Intelligent Systems, Gaithersburg, MD, NIST.

[10] Hall, A. D. (1989). Metasystems methodology: A new synthesis unification. Oxford, England, Pergamon Press.

[11] Hasan, H. (1998). Integrating IS and HCI using activity theory as a philosophical and theoretical basis, Foundations of Information Theory. 2000.

[12] Hanson, R. (2001). Economic growth given machine intelligence, Hason. 2003.

[13] Hazlitt, H. (1979). Economics in one lesson: The shortest and surest way to understand basic economics. New York, NY, Crown Publishers.

[14] Keynes, J. M. (1933). Essays in persuasions. London, UK, Macmillan.

[15] Kienholz, A. (1999). Systems rethinking: an inquiring systems approach to the art and practice of the learning organization. 2001.

[16] Knauf, R. and A. Gonzalez (1997). "A Turing test: approach to intelligent system validation." Leipziger Informatik-Tage 25 (26).

[17] Knauf, R. and A. J. Gonzalez (1997). A Turing test approach to intelligent system validation. Forschungsinstitut fur InformationsTechnologien Leipzig, Leipzig, FIT.

[18] Knauf, R., K. P. Jantke, et al. (1997). Foundamentals of Turing test approach to validation of AI systems. 2002.

[19] Knauf, R., I. Philipow, et al. (1997). Towards an assessment of an AI system's validity by a Turing test, Technical University of Iimanau, Germany

[20] Kurzweil, R. (1999). The age of spiritual machines: When computers exceed human intelligence. New York, NY, Virking.

[21] Lee, S., W. C. Bang, et al. (2000). Measure of system intelligence: An engineering perspective. PerMIS: Workshop on Performance Metrics for Intelligent Systems, Gaithersburg, MD, NIST.

[22] Leontief, W. W. (1982). "The distribution of work and income." Scientific American(192): 188-204.

[23] Lind, R. K. and K. Vairavan (1989). "An experimental investugation of software metrics and their relationship to software development effort." IEEE Transactions on Software Engineering **15**(5): 649-653.

[24] Linstone, H. A. (1984). Multiple perspectives for decision making: bridging the gap between analysis and action. New York, NY, North-Holland.

[25] Lowell, B. E. (1995). A Taxonomy of uncertainty. Systems Science. Portland. OR, Portland State University**:** 635.

[26] Mershin, A., D. Nanopoulos, et al. (2000). "Quantum brain?" arXiv:quant-ph **1**(24): 1-10.

[27] Meystel, A. (2000). Evolution of intelligent systems architectures: What should be measured? PerMIS, Gaithersburg, MD, national Institute of Standard and technology.

[28] Nilsson, N., S. CooK, et al. (1983). Artificial intelligence: Its impacts on human occupations and distribution of income. 8th International Joint Conference on Artificial Intelligence, Karlsruhe, Germany.

[29] Penrose, R. (1994). Shadows of the mind: A Search for the missing science of consciousness. Oxford, Oxford University Press.

[30] Ricardo, D. (1821). On the principles of political economy and taxation. London, UK, Murray.

[31] Sapp, J. C. (1987). Eletricity demand forecasting in a changing reginonal context: The application of the multiple perspectives concept to the prediction process. Systems Science. Portland, OR, Portland State University.

[32] Searle, J. (1989). "Minds, brain, and programs." The Behavioral and Brain Science 3: 417-427.

[33] Senge, P. M. (1990). The fifth discipline: The art & practice of the learning organization. New York, NY, Currency Doubleday.

[34] Simon, H. A. (1977). The new science of management decision. Englewwod, NJ, Prentice Hall.

[35] Szu, H. (2000). Machine IQ with Stable Cybernetic Learning with and without teacher. PerMIS, Gaithersburg, MD, NIST

[36] Tarr, S. C. (1990). The knowledge transfer project: A multiple perspectives investigation into the integration of a new technology within a business unit. Systems Science. Portland, OR, University of Portland.

[37] Turing, A. (1950). "Computing machinery and intelligence." Mind 59 (236): 433-460.

[38] Ulinwa, I. C. (2003). "Insight from a primeval unmanned aircraft." To be published.

[39] Whalem, T. (2000). What is the Value of Intelligence and How Can It Be Measured? PerMIS: Workshop on Performance Metrics for intelligent Systems, Gaithersburg, NIST.

[40] Wolfram, S. (2002). A new kind of science. Champaign, IL, Wolfram Media, Inc.

[41] Zadeh, L. A. (1972). "A fuzzy-set-theoretic interpretation of linguistic hedges." Journal of Cybernetics 2 (3): 4-34.

[42] Zadeh, L. A. (1973). "Outline of a new approach to the analysis of complex systems and\decision process." IEEE Transcations on Systems, Man, and Cybernetics SMC-3 (1).

[43] Zadeh, L. A. (1978). "Fuzzy sets as a basis for a theory of possibility." Fuzzy Sets and Systems **1**: 3-28.

[44] Zeiber, A. R. (1996). A system approach for rational decision making in potential strike situation. Systems Science. Portland, OR, Portland State University**.**